Neuro-Fuzzy Adaptation of Synergistic Control System of Multi-Mode Objects

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Abstract. The article considers the issues of creation of high-efficiency algorithms for control of technological facilities, functioning in conditions of uncertainty. The algorithm of neuro-fuzzy adaptation of fuzzy-logical PID-regulator is proposed, which allows ensuring high speed of the synergistic control system of multi-mode objects due to reduction of the number of iterations during training, that is, the number of neural network training epochs. A fast fuzzy-logic output algorithm has been developed to eliminate empty solutions and zero sections in terms that describe input and output fuzzy variables. A structural diagram of synergistic control systems of multi-mode technological processes has been developed, which includes an adaptation unit, which allows correcting not only the parameters, but also the structures of the control stages. Proposed neuro-fuzzy adaptation in control tasks of technological process equipment allows accelerating process of system training, due to use of high-speed algorithm of fuzzy-logical output, to reduce error of results of training of neuro-fuzzy network from 8 to 1%. An algorithm for training the neural network was developed, based on the use of the soft computation method, using the area difference of the belonging function. Based on the simulation experiment, it is determined that the accuracy of training in the existing methods is about 5%, therefore one parameter must be corrected, by change in the third or fourth layer of the neuro-fuzzy network fuzzy-logical operations, that is, instead of min, use the max operation, which allows to obtain a given result in fewer iterations than in the known methods.

1. Introduction.

One of the main requirements for modern technological facilities is the presence of high-speed operating modes of technological units.

The development of a multi-process synergistic control system of multi-mode objects capable of maintaining the main operating parameters within a given range is a complex multi-criterion optimization task in conditions of uncertainty of the operating characteristics of the control object and the parameters of the external environment. To solve such a complex problem, it is promising to introduce the technology for developing synergistic control systems of multi-mode objects based on a fuzzy regulator with adaptive properties.

Recently, so-called fuzzy control algorithms have become increasingly used in process synergistic control systems of multi-mode objects. Regulators built on this innovative concept are in some cases able to provide higher transient quality indicators than classic regulators. Such structure of the regulator in combination with optimal selection of parameters of fuzzy regulator allows implementation of adaptive synergistic control systems of undefined and non-stationary mechanisms at minimum settings regardless of their structure [1-3]. In addition, using the technology of synthesizing fuzzy control algorithms, it is possible to optimize complex control loops without conducting comprehensive mathematical researches.

Changing the parameters of the functional converter of the regulator allows adjusting both the dynamic and static characteristics of the synergistic control systems of multi-mode objects.

Currently, in synergistic control systems of multi-mode technological processes based on traditional fuzzy-logical output mechanisms, the calculation process has a low efficiency of the resulting value, and all information characteristics are not taken into account [4-7].

Until that time, in synergistic control systems of multi-mode technological processes PID-regulators or regulators implemented on robustly control principles were used. The most significant disadvantage of the above methods is their low speed [8-9]. It should be noted that as the number of monitored parameters increases, the performance of the system also decreases.

To overcome the above problems, the principles of fuzzy-logical control are now widely used, allowing in real time to effectively control the technological process in case of random errors, providing the given quality of process control.

At the same time, the speed of synergistic systems does not exceed several tenths of microseconds, since in order to find a control parameter, it is necessary to manipulate only a single value coming from the sensor system at a given time.

2. Main part.

It is known that at present, in solving the problem, universal approximators of a wide class of multivariate nonlinear functions are generally used – adaptive models of fuzzy-logical output and adaptive fuzzy-neural networks. In this case, the parameters of adaptive models are adjusted by optimizing them in the given criteria, according to the training selection.

In this case, the solution of the set optimization problem encounters some difficulties associated with the large dimension of vector of the fuzzy model parameters and the space of search for the extremity of the target function.

Currently, it has a lot of experience in solving optimization problems.

It should be noted that standard and widely used are gradient optimization methods that using to find the extremum of the function gradient. The main disadvantage of these methods is the dependence of the calculation of the function gradient on the initial approximation. Another common method of optimization is the random search method, where the function gradient is replaced by a random vector.

These difficulties are overcome using genetic algorithms in the problems of optimization methods [10].

To solve problems of multicriterial optimization, in the work [11-15] the use of evolutionary computation methods is proposed, to improve the efficiency of training algorithms of fuzzy models, using dynamic changes of optimization algorithm parameters.

Such properties are characteristic of artificial immune systems, such as recognition, training, self-tuning, structure tuning, and so on [16-19].

In the work [20] in fuzzy systems, the use of artificial immune systems capable of generating a base of fuzzy rules is proposed. At the same time, on the basis of artificial immune systems, it is possible to set up adaptive models of fuzzy output, presented in the form of a fuzzy-neural network and a fuzzy-logic output system.

The proposed immune system algorithms are able to adapt for fuzzy models of nonlinear dynamic objects.

However, practical implementation of traditional fuzzy-logic algorithms, used in various synergistic control systems of multi-mode objects, has insufficient connection with reduced output time of the resulting knowledge of model or control signals.

On the other hand, the implementation of conventional fuzzy-logic algorithms, used in various intelligent synergistic control systems of multi-mode objects, has a number of drawbacks in reducing the output time of the resulting value.

The above is related to the fact that, firstly, the availability of empty solutions, the number of which increases with the increase in the number of fuzzy rules, forms the basis of the knowledge base. Empty solutions appear in inferences of fuzzy-logical leads during search of terms of input variables depending on specific control rules, however, they do not participate in further mathematical calculations, but significantly reduced speed of a synergistic control system of multi-mode objects.

Secondly, is the presence of zero sections in terms, describing input and output fuzzy variables, that appear during the program implementation of fuzzy-logical output algorithms. That is, when it is necessary to perform the operation of taking the maximum and/or minimum between two terms, the program sequentially navigates along the abscissa axis all possible values of the fuzzy variable through a certain step all possible values of fuzzy variable, defined on a universal set, and not only those values of the universal set where the value of the belonging function (ordinate values) is different from zero.

In this regard, one of the most relevant is the task of eliminating the appearance of empty solutions and zero sections.

2.1. Solution concept.

In the article to eliminate the above mentioned disadvantages, a fast-acting fuzzy-logic output algorithm is proposed, which allows eliminating empty solutions and zero sections in terms describing input and output fuzzy variables.

Based on the above, the fuzzy-logic output algorithm, which ensures that the above-requirements are met, consists of the following steps:

1. Creates a membership function for input and output variables.
2. Create fuzzy control rules that describe the relationship between input and output parameters.
3. Calculation of values of truth degrees for each fuzzy control rule.
4. Create a knowledge base that describes the relationship between input and output system variables.
5. Input of information from sensors.
6. Define of truncated coefficients for conclusions.
7. Calculate truncated levels to determine the fuzzy-logic output mechanism.
8. Define truncated belonging functions for conclusions of the fuzzy-logic output mechanism.
9. Merging truncated belonging functions.
10. Defuzzification.
11. Removal of output parameter.

The increase in speed is ensured by reducing the number of conclusions, since the number of conclusions in the proposed algorithm will be equal to the number of terms, and in traditional algorithms the number of conclusions will be equal to the number of terms of input variables raised to a degree equal to the number of input variables [21].

The proposed algorithm is particularly effective in solving the problem of predicting the behavior of dynamic objects.

Taking into account given above, in work the block diagram of the synergistic control systems of multi-mode technological processes (figure 1), which is turning on the adaptation block in the structure, presented for correction not only parameters, but also structure of control stages is offered.

In the adaptation unit corrects not only the parameters, but also the structure of the control laws, that is, the entire synergistic control system as a whole. The adaptation unit consists of the following units: «Output mechanism», «Assessment of the state of the control object», «Knowledge base», «Adaptation mechanism».

In order to reduce the training results, the following neuro-fuzzy network was developed based on the proposed fast-acting fuzzy-logic output algorithm consisting of six layers. The first layer is designed to fuzzification input variables, each of which has two terms of belonging function. The number of nodes of the first layer is equal to the number of terms of the three input variables. At the output of the second layer, values of the degree of belonging of the input variables are determined, determined on the basis of information received from sensors. In the third layer, the degree of data truth is determined based on fuzzy control rules. On the fourth and fifth layers, knowledge of the belonging function is determined, and on the sixth, process of defuzzification of output parameter is performed – the value of the control signal is carried out.

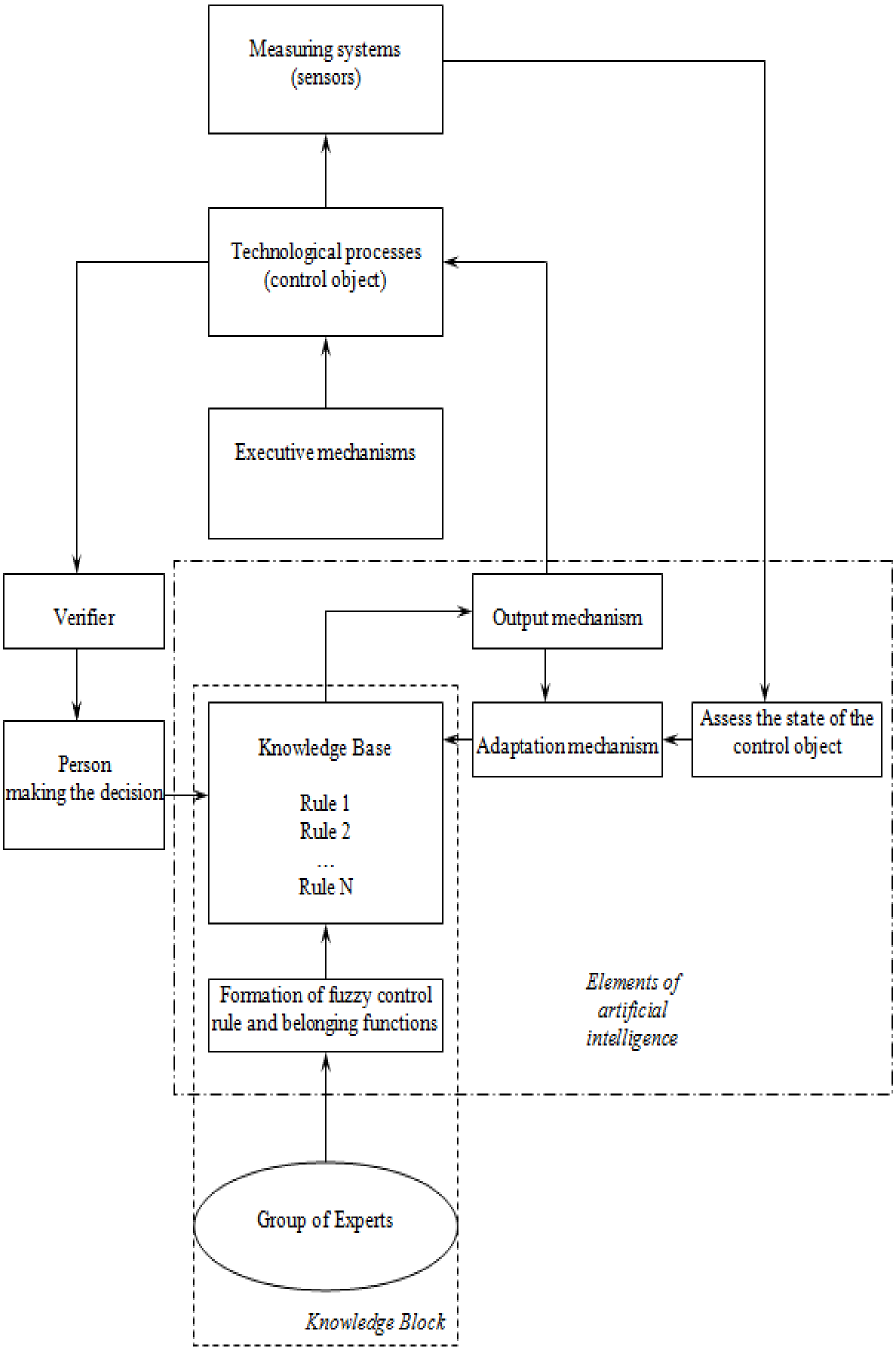

Figure 1 - Structure of the synergistic control system of multi-mode objects with neuro-fuzzy adaptation.

An advantage of the developed neuro-fuzzy network is that the fourth layer has fewer outputs, which increases the speed of control decisions. At the same time in the fourth layer operations in adaptive neuro-fuzzy output system, operating on the basis of mechanism of fast algorithm of fuzzy-logical output are reduced by 2 times compared to traditional ANFIS.

This network works as follows. During control, information from sensors is supplied to output unit and to state estimation unit. Then, from the output unit and the state estimation unit, the obtained values of the control parameter are supplied to the «adaptation» unit, in which, in turn, the reference value of the control parameter is set.

The adaptation unit calculates the control parameter in real time and compares the calculated and reference values. And if they do not coincide, then adapts the results to the standard values, after which it generates control signals.

2.2. Example solution.

Let the following data come from the system of active control of the equipment of the object: a = 15, b = 26. Degree of belonging for each prerequisite will be:

$\alpha_{11} = 1$; $\alpha_{12} = 0{,}04$; $\alpha_{13} = 0{,}76$;
$\alpha_{21} = 1$; $\alpha_{22} = 0{,}15$; $\alpha_{23} = 0{,}94$;

There are truncated levels for each prerequisite of the fuzzy control rule:

α_1 = min (l, 0,04, 0,76)=0,04;
α_2 = min (1, 0,04, 0,94)=0,04;
α_3 = min (l, 0,15, 0,76)=0,15;
α_4 = min (l, 0,15, 0,94)=0,15;
α_5 = min (l, 0,04, 0,76)=0,04;
α_6 = min (l, 0,04, 0,94)=0,04;
α_7 = min (l, 0,15, 0,76)=0,15;
α_8 = min (l, 0,15, 0,94)=0,15.

Truncated levels are calculated:

$y_1' = 0{,}04$;
y_2' = min (0,04, 0,15 0,04)=0,04;
y_3' = min (0,15 0,04 0,15)=0,04;
$y_4' = 0{,}15$;

Next are truncated belonging functions, and based on the center of gravity method, control solutions are determined:

y'' = 32,25;
p' = 86,98 + 0,13v – 15,6 s.

Let the given value be y_{giv} = 38, the output value of the neuro-fuzzy network is calculated: $y_1^{''}$ = 39.83. It can be seen that after the first iteration of the training, the error between the two values is already 39.83 – 38 = 1.83. The resulting value is $y_{10}^{''}$ = 36.98.

The results obtained showed that after 10 iterations, the accuracy of training is about 5%, therefore, it is necessary to correct one parameter. In this case, it is advisable to change fuzzy-logical operations in the third or fourth layer of the neuro-fuzzy network – instead of min, use the max operation. Then, to obtain a specified result of y_{giv} = 38, would be required 15 iterations, which is one more than in the above example.

3. Conclusion.

Thus, the proposed neuro-fuzzy adaptation in process equipment control tasks allows reducing the number of iterations during the training of the fuzzy-logic output algorithm, accelerating the system training process due to the fast-acting fuzzy-logic output algorithm, reducing the error of the results of training of a neuro-fuzzy network from 8 to 1%. A neural network training algorithm based on the use of the soft computing method has been developed.

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